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The Association of Parent-Reported Executive Functioning, Reading, and Math Is Explained by Nature, Not Nurture

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According to the hybrid model (van Bergen, van der Leij, & de Jong, 2014), the significant association among executive functioning (EF), reading, and math may be partially explained by parent-reported EF's role as a common risk and/or protective factor in reading and math (dis)abilities. The current study used a sample of 434 twin pairs (M_{age} = 12.12) from Florida to conduct genetically sensitive modeling on children's parent-reported EF, reading, and math skills to determine the common and unique etiological influences among the three domains. EF was measured through parent report and reading and math were measured with standardized test scores drawn from Florida's Progress Monitoring and Reporting Network as well as standardized parent-administered assessments collected by mail. Our trivariate Cholesky modeling showed that no matter which parent-reported EF component was modeled, the overlap of parent-reported EF with reading and math was explained by common genetic influences. Supplemental analysis suggested that this might in part be due to general parent report of problem behaviors. Additionally, significant environmental influences, with higher shared environmental overlap than previous work, were also found for reading and math. Findings indicate that poor parent-reported EF is a common cognitive risk factor for reading and math disabilities, which is driven by a shared genetic basis among all three domains.

Keywords: executive functioning, reading, math, twins

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During a single class, schoolchildren are expected to sit in their seats and not speak out of turn, while following multistep instructions, alternating attention between different assignments, and integrating new and previously learned information on demand (Gathercole, Lamont, & Alloway, 2006). The coordination of such complex demands requires a high degree of self-regulatory ability in order to adapt one's thoughts and actions to respond to current contextual needs. The mechanism that drives goal-directed self-regulation, like controlling one's behavioral impulses based on classroom rules or focusing one's attention to listen to a teacher's lesson, is hypothesized to be the brain's central executive, or executive functioning (EF; Baddeley, 1998). Specifically, EF represents the processing efficiency of an individual's cognitive control system (Stanovich, 2009; Toplak, West, & Stanovich, 2013), which is driven by prefrontal cortex functioning (Welsh & Pennington, 1988; Welsh, Pennington, & Groisser, 1991), and proffers individuals with the ability to adapt their cognitive processes and behaviors to their present goals (Toplak et al., 2013).

In terms of academic achievement, EF has been shown to have significant associations with both reading (Daucourt, Schatschneider, Connor, Al Otaiba, & Hart, 2018) and math (Clark, Pritchard, & Woodward, 2010), which may be attributable to EF's role as a common cognitive risk and protective factor among learning (dis)abilities. In support of the principle of common underlying causes among learning disabilities, previous work on reading and math has shown that students already experiencing an academic skill deficit in one domain are four to five times more likely to experience a deficit in an additional academic domain compared to typically developing students (Landerl & Moll, 2010). On the other hand, high EF skills may help children do well in both the reading and math domains (Ten Eycke &

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Dewey, 2016). Thus, the present investigation aims to examine whether EF is a potential common risk and/or protective factor driving the above-chance comorbidity among reading and math (dis)abilities.

When examining the role of EF in the overlap of reading and math (dis)abilities, it is important to consider how EF is measured. Previous work has shown that the associations between EF and reading and EF and math differ based on whether EF skills are measured with report-based or performance-based assessments. Recently, which of these two methods is best has become a point of empirical debate due to the low-magnitude correlations ($rs \sim .10–.30$) found between them (McAuley, Chen, Goos, Schachar, & Crosbie, 2010). In fact, many researchers argue that report-based assessments measure self-regulatory abilities enabled by EF, rather than EF itself, and that EF itself can only fully be captured by a battery of performance-based measures (Malanchini, Engelhardt, Grotzinger, Harden, & Tucker-Drob, 2018; Toplak et al., 2013). In contrast, others argue that because the organization and structure is provided by the experimenter with performance-based measures, they do not adequately measure a person's ability to pursue long-term goals in the real world (Nęcka, Gruszka, Orzechowski, Nowak, & Wójcik, 2018). This distinction between performance- and report-based EF measures is akin to the distinction between maximal and typical performance (Goff & Ackerman, 1992; Nęcka et al., 2018). Performance-based EF assessments capture the precise performance during testing that is characteristic of EF and report-based measures capture everyday manifestations of self-control abilities that are enabled by EF. The present investigation is not aimed at addressing the debate about EF measurement, but given the lack of common variance between the different assessment methods, we are referring to our assessment of EF in the present investigation as "parent-reported EF," in order to prevent the conflation of the constructs captured by performance- versus report-based EF assessments.

A theoretical framework that supports the existence of common causes, like parent-reported EF, to explain the co-occurrence of learning (dis)abilities is the hybrid model (van Bergen et al., 2014), which combines the multiple deficit model (Pennington, 2006) and the generalist genes hypothesis (Plomin & Kovas, 2005). The hybrid model posits that learning (dis) abilities are driven by underlying etiological (genetic and environmental) risk and/or protective factors, which manifest at the neurological, cognitive, and/or behavioral levels and can be either common or unique among abilities and disorders (see Figure 1). Common etiologies drive the above-chance comorbidity among learning abilities and disorders, while unique etiological risk and protective factors distinguish learning (dis) abilities from one another (van Bergen et al., 2014). Rather than relying on indirect etiological measures, like the family history questionnaires used in prior work (Landerl & Moll, 2010), we utilized a sample of twins to statistically quantify the genetic and environmental influences on and among parent-reported EF, reading, and math. This allows us to capture three of the four levels of analysis proposed by the hybrid model. Our genetically sensitive analyses represent the etiological level (top row of Figure 1), while the everyday behavioral manifestations of cognitive control captured by parent-reported EF represent the cognitive level (third row of Figure 1) and reading and math ability represent the behavioral level (bottom row of Figure 1).

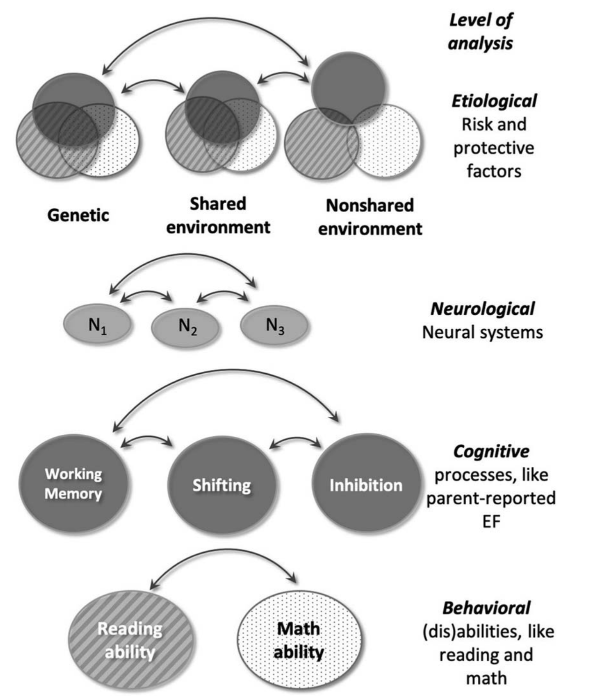

Figure 1. The theoretical framework used in the current study is the hybrid model for learning (dis)abilities (adapted from van Bergen et al., 2014). Each circle in the top row represents one of the three skills under investigation: parent-reported EF, reading, and math ability. Potential overlap at the etiological level is graphically presented as Venn diagrams for each of the three sources of biometric variation: genetic (rA), shared environmental (rC), and nonshared environmental (rE). Double-headed arrows indicate correlations. Causal connections between levels of analyses are omitted. In the second row, N_i represent neural systems, which were not included in the present study. Working memory, shifting, and inhibition represent parent-reported executive functioning components. Adapted with permission from "The Intergenerational Multiple Deficit Model and the Case of Dyslexia" by E. van Bergen, A. van der Leij, & P. F. de Jong, 2014, *Frontiers in Human Neuroscience, 8,* 346. Copyright, 2014 by E. van Bergen, A. van der Leij, & P. F. de Jong.

Although the existence of common genetic and, to a lesser extent, shared environmental factors between reading and math is well established (Daucourt, Erbeli, Little, Haughbrook, & Hart, 2020; Hart, Petrill, Thompson, & Plomin, 2009), the nature of the association of EF with reading and math has not been studied extensively, and the work that does exist has shown less consistent findings overall. One report has examined the role of performance-based EF with prereading and premath skills in preschoolers, finding that after accounting for variance shared with general cognitive ability, performance-based EF tasks showed significant shared environmental, but not genetic, overlap with prereading and premath skills (Fujisawa, Todo, & Ando, 2019). However, given that nested model comparisons indicated that only (shared and nonshared) environmental influences should be modeled for performance-based EF, the lack of common genetic influences among EF, reading, and math was not surprising (Fujisawa et al., 2019). In contrast, recent work examining the etiological architecture of EF found that only genetic and nonshared environmental influences on report-based EF were supported (Little et al., 2017), a finding that has been echoed in studies using task-based measures of EF (Friedman et al., 2008; Malanchini et al., 2018). Another article examined the association of EF with math and reading separately for each domain, rather than all three together. They found overlapping genetic influences of the same magnitude, between performance-based EF and reading and performance-based EF and math (Malanchini et al., 2018). However, when modeling a report-based, EF-related measure of impulse control, this work did not find overlapping etiological influences with reading or math (Malanchini et al., 2018). Our work will be the first to simultaneously analyze report-based EF, reading, and math together. This will contribute to our understanding of how EF is associated with reading and math, informed by the hybrid model, which indicates that common etiological risk and/or protective factors are likely driving the co-occurrence of EF, reading, and math skills.

For this work, we test the etiological association of EF with reading and math, using parent-reported EF assessed by the Behavior Rating Inventory of Executive Functioning (BRIEF; Gioia, Isquith, Guy, & Kenworthy, 2000), a measure meant to tap into observable everyday manifestations of EF ability. The BRIEF is likely to be more aligned with the executive demands of a classroom setting than performance-based EF measures that occur in highly controlled laboratory settings (Clark et al., 2010; Gioia, Isquith, Kenworthy, & Barton, 2002; Isquith, Crawford, Espy, & Gioia, 2005). In fact, individuals who show impaired EF abilities based on their BRIEF scores do not show the same impairment on task-based EF measures due to the assistance of experimenter cues and precise instructions. This supports the idea that the high degree of examiner control in task-based EF measures may not be capturing real-world EF ability (Gioia et al., 2002). Furthermore, in comparison to task-based EF measures, report-based EF measures have been shown to produce more reliable individual differences (Hedge, Powell, & Sumner, 2018). In addition, rather than having a zeroed-in focus on just one self-regulatory ability, like impulse control, the BRIEF captures many different kinds of self-regulatory behavior enabled by EF. Interestingly, the BRIEF has been shown to have a similar etiological architecture to performance-based EF measures (Little et al., 2017). This may indicate that the EF captured by the BRIEF is more etiologically similar to the EF captured by performance-based measures than other questionnaire-based EF instruments, and the current investigation may still serve to inform future etiological investigations of EF using performance-based tasks. Based on the generalist genes hypothesis tenet that mostly overlapping genes underlie all learning-related abilities (Plomin & Kovas, 2005), we expect common genetic influences among parent-reported EF, reading, and math. We also expect common shared environmental influences between reading and math that may or may not overlap with parent-reported EF (Hart, Petrill, Willcutt, et al., 2010).

When defining EF using our parent-report measure, we used the most common conceptualization of EF used in the performance-based EF literature, a three-component model comprised of working memory (WM), shifting, and inhibition (Miyake et al., 2000). This decision was based on evidence from genetically unrelated individuals that the association of parent-reported EF with reading and math performance varies based on which of these three components is measured (Clark et al., 2010). Therefore, we expect potentially differing etiological relations for the three subscales due to the potential explanation that the divergent phenotypic associations with reading and math are driven by different underlying etiologies. First, "WM" refers to the ability to hold and manipulate information based on the present context (St. Clair-Thompson & Gathercole, 2006). Parent-reported WM, as measured by the BRIEF, has demonstrated significant associations with reading comprehension and math fluency separately (Clark et al., 2010), indicating that parent-reported WM, reading, and math may have common underlying etiologies when all three are modeled together. Conversely, "shifting," which is the ability to move back and forth between conceptual representations in order to select and maintain appropriate strategies and disengage from inappropriate ones (Yeniad et al., 2013), did not correlate significantly with reading or math when parent-reported shifting was measured by the BRIEF (Clark et al., 2010). Thus, if truly unrelated, parent-reported shifting would not have any significant overlapping etiological influences with reading, math, or both. Finally, "inhibition" captures the ability to deliberately stop dominant, automatic responses in place of more appropriate responses (St. Clair-Thompson & Gathercole, 2006). In the same vein as WM, parent-reported inhibition based on the BRIEF has demonstrated significant associations with reading and math, separately (Clark et al., 2010). Therefore, overlapping etiological influences may also be found among parent-reported inhibition, reading, and math.

Finally, after examining the role of the three-component model of EF, our analytical approach mirrored the common practice in performance-based EF studies of accounting for the "unity and diversity" of executive functions by creating a single latent factor of parent-reported EF (Friedman & Miyake, 2017; Malanchini et al., 2018). Specifically, we loaded parent-reported WM, shifting, and inhibition scales onto a latent factor of parent-reported EF in order to separate the common executive variance among all three parent-reported EFs from the unique variance captured by each parent-reported scale. Thus, we ran four trivariate models, one for each separate parent-reported EF component (WM, shifting, inhibition) with reading and math, and a fourth model with a latent factor of parent-reported EF, reading, and math. This will allow us to test whether different etiological relations are found when each separate parent-reported EF component versus the common executive variance among all three parent-reported EF components is modeled.

Although our motivation for using the hybrid model framework was to examine how common risk factors among reading and math disorders contribute to their comorbidity, the hybrid model posits that etiological influences also serve as protective factors that are associated with positive learning outcomes. In line with this conceptualization that the etiological influences on ability and disability are not distinct, one of the most highly replicated findings in the twin literature is that the same genetic and environmental influences are found for ability and disability, which simply represent different ends of the same distribution of ability (Plomin, DeFries, Knopik, & Neiderhiser, 2016). Accordingly, for the present analysis, we used the full distribution of parent-reported EF, reading, and math ability to avoid imposing arbitrary cutoffs on our variables.

In sum, according to the hybrid model's principle of common risk and protective factors, and evidence that parent-reported EF is significant factor in reading and math outcomes, we believe that parent-reported EF may partially explain the etiological overlap between reading and math. By using a sample of twins, we will examine the influences on and among parent-reported EF, reading, and math at the etiological, cognitive, and behavioral levels. Based on the generalist genes hypothesis, we expect the variance shared by parent-reported EF with reading and math to be mostly genetic. Given that parent-reported EF is probably not the only risk and/or protective factor they have in common, we anticipate additional variance shared between reading and math not accounted for by parent-reported EF. Additionally, based on the hybrid model tenet of common risk and/or protective factors in learning-related (dis)abilities, we expect similar overlapping etiological influences among parent-reported EF, reading, and math for all subcomponents of parent-reported EF as well as for a latent factor of parent-reported EF.

Method

Participants

The Florida Twin Project on Reading, Behavior, and Environment ("FTP"; Taylor, Martinez, & Hart, 2019) is a cross-sequential study that combines questionnaire-based assessments of twins' behavior, environmental contexts, and reading and math achievement (for more information about the sample ascertainment method, please see Taylor & Schatschneider, 2010). In brief, twins were identified by locating individuals that matched on last name, date of birth, and school in Florida's Progress Monitoring and Reporting Network (PMRN), a statewide standardized achievement test database for all public-school children. Once twin status was confirmed, twin zygosity was determined using a five-item parent-report questionnaire on physical likeness (Lykken, Bouchard, McGue, & Tellegen, 1990). The achievement data is a combination of standardized, parent-administered reading and math assessments collected by mail and reading achievement data from the PMRN. For the current study, data were available from 171 monozygotic (MZ; 53.22% female pairs) and 263 dizygotic (DZ; 39.54% same-sex female pairs, 29.66% same-sex male pairs, 30.80% opposite sex pairs) twin pairs, who were approximately 12 years old (M_{age} = 12.12, SD = 2.49, range = 6.74–17.03). The racial composition of the sample was retrieved from the PMRN and comparable to percentages reported for the state of Florida by the U.S. Census Bureau. The sample included 56.28% White, 13.29% African American, 22.46% Hispanic, 0.97% Asian, 3.62% Mixed, and 0.97% Native American/Pacific Islander. Maternal education levels varied widely: 15.89% had a high school or equivalent education or less, 20.09% had completed some college, 12.15% had graduated from 2-year college, 22.90% graduated from 4-year college, 28.50% had some postgraduate training or a graduate or professional degree. The household income reported in our sample also had a high degree of variability with 16.15% below $25,000, 18.06% ranging from $25,000 to $49,999, 36.34% ranging from $50,000 to $99,999, and 29.45% reporting income of $100,000 or more. All twin pairs were moved forward into analyses in order to maximize the ecological validity of the results obtained, but due to the voluntary nature of the questionnaires and the method of data collection employed, complete data were not available on each measure for the entire sample (see Table 1 for *n*'s).

Procedure

The data used in the present study came from the second wave of questionnaire data collection from the FTP, which spanned the 2013–2014 school year. Parent-reported executive functioning (EF), assessed by the WM, shifting, and inhibition subscales of the parent-report version of the BRIEF (Gioia et al., 2000), two reading measures, namely the Gates MacGinitie reading comprehension test ("GM"), and the Test of Silent Reading Efficiency and Comprehension ("TOSREC"), and a math achievement measure, the Woodcock Johnson-III Tests of Achievement math fluency subtest ("math fluency"), were mailed home as part of a questionnaire packet to be filled out by parents and twins. The questionnaire achievement measures (i.e., GM, TOSREC, and Math Fluency) were completed by the twins and administered by their parents in the home, according to a standardized protocol we provided. The Florida Comprehensive Assessment Test ("FCAT") was given by trained test administrators as part of normal school attendance according to schedules set by the Florida Department of Education and local school districts. FCAT scores were subsequently entered into the PMRN, and children's unique identifiers given by the state of Florida were used to match twins' questionnaire data to their FCAT scores. All available data from the spring collection period for the included measures were used for this study. All parents of twins provided informed consent for inves-

Table 1
Descriptive Statistics

Measure	*n*	*M*	*SD*	Min	Max	Skew	Kurtosis
Parent-reported WM	862	14.63	4.63	10.00	30.00	1.07	0.56
Parent-reported shifting	862	11.54	3.30	8.00	24.00	1.02	0.82
Parent-reported inhibition	861	13.20	3.81	10.00	30.00	1.48	2.03
FCAT	703	237.67	25.19	155.00	296.00	−0.32	−0.01
GM	847	33.81	9.25	0.00	48.00	−0.83	0.18
TOSREC	837	37.58	13.01	0.00	70.00	0.23	−0.28
Math Fluency	669	86.25	28.19	7.00	150.00	−0.04	−0.49

Note. Parent-reported WM = parent-reported working memory; FCAT = Florida Comprehensive Assessment Test reading subtest; GM = Gates MacGinitie Reading Tests comprehension subtest; TOSREC = Test of Silent Reading Efficiency and Comprehension; Math Fluency = Woodcock Johnson-III Tests of Achievement math fluency subtest. Sample size (*n*) reflects individuals. Analyses were conducted on raw data.

tigators to use their twins' PMRN data, and twins provided assent to participate as approved by the Florida State University Institutional Review Board under title: "The Florida Twin Project on Reading, Behavior, and Environment" and protocol number 2019.28660.

Measures

Behavior Rating Inventory of Executive Function (BRIEF). The parent form of the BRIEF is an 86-item, standardized rating scale developed to assess the everyday behavioral manifestations of children's executive control functions (Gioia et al., 2000). Using a 3-point Likert scale (*never*, *sometimes*, *often*), parents were asked to report on whether their child had exhibited a list of distinct problem behaviors over the past 6 months. Each item loads onto one of eight subscales (inhibit, shift, emotional control, initiate, working memory, plan/organize, organization of materials, and monitor), and for the present report, the working memory ("WM"), shift ("shifting"), and inhibit ("inhibition") subscales were used in line with the most common conceptualization of EFs (Miyake et al., 2000). For ease of interpretation, scores were reverse-scored (multiplied by −1) after descriptive statistics were calculated, so that high BRIEF scores would reflect high parent-reported EF and low BRIEF scores would reflect low parent-reported EF. Reliabilities in this sample for all three scales were adequate (Cronbach's alphas: WM = .70, shift = .75, and inhibit = .72).

Florida Comprehensive Assessment Test 2.0 reading subtest (FCAT). The FCAT reading subtest is a criterion-referenced, high-stakes assessment given each May to Grades 3–10 that measures student grade-level reading progress based on reading content, knowledge, and skills. The questions require multiple-choice responses based on descriptive passages, and the developmental scaled scores range from 140 to 302, with alternate form reliabilities ranging from .86 to .91 (Florida Department of Education, 2011).

Gates MacGinitie Reading Tests comprehension subtest (GM). The GM is a norm-referenced reading comprehension assessment comprised of 48 multiple-choice questions, which is available in alternate forms for kindergarten through Grade 12. The items include both explicit and implicit questions based on narrative and expository passages with an allotted time of 35 min for completion. The alternate form reliabilities of the comprehension subtest range from .87 to .92 (MacGinitie, MacGinitie, Cooter, & Curry, 1989). The Cronbach's alpha for the GM in the current sample was .88.

Test of Silent Reading Efficiency and Comprehension (TOSREC). The TOSREC is a 50-item, norm-referenced, standardized test that assesses silent reading and comprehension of connected text. Each item measures speed and accuracy by presenting a sentence that must be evaluated as true or false, with the participant given 3 min to complete as many as possible. The TOSREC is utilized for screening, progress monitoring and research purposes and has alternate forms across all grade levels with reliability coefficients of .85 and higher (Wagner, Torgesen, Rashotte, & Pearson, 2010). In order to control for guessing, total scores were calculated by subtracting the number of incorrect responses from the number of correct responses. The Cronbach's alpha for TOSREC in our sample was .88.

Woodcock Johnson-III: Tests of Achievement math fluency subtest ("math fluency"). The math fluency subtest is a norm-referenced, timed assessment that measures numerical aptitude through rapid application of simple arithmetic procedures, including basic addition, subtraction, and multiplication (McGrew, Woodcock, & Schrank, 2007). The test-taker is given 3 min to answer as many questions as possible out of 160 total items. For students 7–11 years old, the test–retest reliability reported in the 2001 test manual is .95 (Mather, Wendling, & Woodcock, 2001). Our analyses utilized the raw score for Math Fluency, which was calculated by tallying the total number of correct responses. A total of 187 twins' math fluency scores was excluded from our final analyses due to not being timed.

Data Analyses

As a first step, descriptive statistics were generated for all EF, reading, and math variables. Next, in order to control for differences attributable to age and sex, data were regressed on age, age-squared, and sex (McGue & Bouchard, 1984). Subsequently, Pearson correlations were calculated. Then, twin intraclass correlations (ICCs) and cross-twin cross-trait correlations (CTCTs), by zygosity, were calculated for each measure. The comparative magnitudes of the ICCs between monozygotic (MZ) twin pairs, who share 100% of their segregating genes, and dizygotic (DZ) twin pairs, who share 50% of their segregating genes, provide a preliminary indication of the etiological effects for each measure. Genetic influences represent the additive genetic influences inherited from parents (nonadditive genetic influences were not modeled here), and shared environmental and nonshared environmental influences represent any environmental influences that make twins more similar (i.e., home and school) and more different (i.e., different peer groups), respectively. Additive genetic influences are indicated on a trait when MZ twin intraclass correlations are higher than those of the DZ twins. The extent to which MZ twin intraclass correlations are less than twice the magnitude of DZ twin intraclass correlations indicates shared environmental influences on that trait. Nonshared environmental influences are indicated when MZ twin pairs are not perfectly correlated with one another. As a final preparatory step for twin modeling, all data were *z*-scored to prepare for structural equation modeling. All preliminary analyses were conducted in SAS 9.4.

Following the preliminary analyses, structural equation modeling was conducted to assess the univariate genetic and environmental influences on all variables and the genetic and environmental influences on the covariation among parent-reported EF, reading, and math. Cholesky decomposition models were run to partition the covariation among the three variables into a series of biometric latent factors representing additive genetic (A), shared environmental (C), and nonshared environmental (E) influences. In total, four trivariate Cholesky decomposition models were run, one for each separate parent-reported EF component as a measured variable (WM, shifting, and inhibition) and a fourth model analyzing a latent factor of parent-reported EF (comprised of the three parent-reported EF measures), assessing the etiological covariation among the parent-reported EF component being analyzed, reading, and math. For all four models, the three reading measures (FCAT, GM, TOSREC) were loaded onto a single latent factor for reading, in order to reduce measurement error and more fully capture the reading construct (Gayán & Olson, 2003). Given that a single math assessment was available for analysis, math fluency was included in all models as a single measured variable.

There were three sets of biometric latent factors estimated in each model. The first set of biometric latent factors (A_1, E_1) represented the additive genetic and nonshared environmental influences common among parent-reported EF, reading, and math. Shared environmental influences common among parent-reported EF, reading, and math (i.e., C_1) were not modeled as MZ ICC's were found to be more than twice as large as DZ ICC's for the parent-reported EF variables, indicating that dominance genetic effects, and/or rater bias or sibling interaction effects were at play for EF (Neale & Cardon, 1992). Dominance genetic effects are nonadditive genetic influences, rater bias effects are when parents contrast their dizygotic twins' behavior based on their perception of zygosity, rather than their twins' actual behavior, and sibling interaction effects are when siblings behave in opposing ways on a trait in order to differentiate from one another. All three effects have the same result of reducing the DZ ICC in comparison to the MZ ICC. The ICC's for the reading and math variables showed patterns of additive genetic, shared environmental and nonshared environmental influences; however, methodological limitations of twin data like the current data dictate that dominance genetic influences and/or rater bias/sibling interaction effects cannot be modeled at the same time as shared environmental influences because the models become unidentified. Thus, the most parsimonious model, in which only additive genetic and nonshared environmental influences are modeled, was chosen (Neale & Cardon, 1992). Importantly, a study exploring the BRIEF's etiological factor structure with a previous wave of data from the FTP found the same pattern of ICC's for the parent-reported WM, shifting, and inhibition scales (Little et al., 2017). Specifically, the study found that the AE model was the best fit for the parent-reported shift scale and the AE-b model that included rater bias/sibling interactions effects was the best fit for the parent-reported inhibit and WM scales (Little et al., 2017), results which were replicated when we tested the AE-b model in the current wave of FTP data. However, since rater bias/sibling interactions effects cannot be modeled at the same time as shared environmental effects, and the reading and math constructs did not show evidence of the same contrast effects, only the AE model was run on the BRIEF scale variables in order to remain consistent and enable trivariate modeling. In support of this methodological decision, recent work examining the etiological influences on the covariation of parent-reported EF, reading, and math also found the AE model to be the best fitting model for EF, whether observation- or questionnaire-based measures were used (Malanchini et al., 2018).

The second set of biometric latent factors (A_2, C_2, E_2) represented the additive genetic, shared environmental, and nonshared environmental influences common for reading and math, after accounting for the common genetic and environmental influences among parent-reported EF, reading, and math. Finally, the last set of biometric latent factors (A_3, C_3, E_3) represented the unique genetic, shared environmental, and nonshared environmental influences on math, after accounting for the first two sets of biometric latent factors. Notably, the order in which variables are presented in a Cholesky decomposition is meaningful for model interpretation and comparable to the importance of variable order in a hierarchical regression (Malanchini et al., 2018). Thus, we modeled parent-reported EF as the first variable in order to test our hypothesis that the significant associations among parent-reported EF, reading, and math ability are explained by common genetic and environmental influences, represented by the first set of biometric factors (A_1, E_1). The structural equation models were all run in Mplus 7.31 (Muthén & Muthén, 2018), using maximum likelihood estimation. Parameter estimates were deemed significant when 95% confidence intervals did not bound zero.

Supplementary Analyses

In response to an editor request, we also conducted supplemental models that controlled for parent-reported problem behaviors. Given our use of a parent-report measure to capture children's EF skills, we ran these supplemental analyses in order to isolate children's specific cognitive EF skills from their parents' overall perception of their children (Abikoff, Courtney, Pelham, & Koplewicz, 1993; Duckworth & Yeager, 2015). To accomplish this, BRIEF scores were residualized on parent-reported problem behaviors and then all analyses were rerun with these new residualized BRIEF scores. The description of the parent-reported problem behaviors measure and detailed results and figures are presented in the online supplemental materials.

Results

Descriptive statistics are presented in Table 1 for the parent-reported EF, reading, and math measures. Pearson correlations are presented in Table 2, showing significant and positive correlations between all variables, with the exception of the correlation between parent-reported shifting and math fluency (p = .067). Among the parent-reported EF components, parent-reported WM exhibited the highest magnitude correlations with all reading and math measures, which is consistent with previous work showing a pronounced role, compared to other components of parent-reported EF, for parent-reported WM in math (Clark et al., 2010). ICCs and CTCT correlations are presented in Table 3. All ICCs were significant, and MZ twin ICCs were consistently greater than DZ twin ICCs across all measures, suggesting genetic influences on each measure. The MZ twin ICCs were also less than twice the magnitude of the DZ twin ICCs for the reading and math fluency measures, indicating shared environmental influences. For the EF components, the MZ ICCs were greater than double the DZ ICCs, suggesting dominance genetic influences rather than shared environmental influences. However, based on limitations related to model identification and the results of a previous data collection wave using the BRIEF measure (Little et al., 2017), which found that the AE model was a better fit than an ADE model, the more parsimonious AE model was used. The MZ twin ICCs were not perfectly correlated for any measure, which suggests that nonshared environmental influences were present.

Results from univariate twin analyses are presented in Table 4. The results indicated that additive genetic factors significantly explain variance in each of the measured variables (h^2 = .35–.75). Furthermore, results show that shared environmental influences are significant for the math and reading measures (c^2 = .28–.40), and nonshared environmental influences are significant for all

Table 2
Pearson Correlations Among Parent-Reported EF, Reading, and Math Measures

Measure	Parent-reported WM	Parent-reported shifting	Parent-reported inhibition	FCAT	GM	TOSREC
Parent-reported WM	—	—	—	—	—	—
Parent-reported shifting	0.57** n = 860	—	—	—	—	—
Parent-reported inhibition	0.60** n = 860	0.54** n = 859	—	—		—
FCAT	0.24** n = 695	0.14** n = 695	0.22** n = 695	—	—	—
GM	0.29** n = 835	0.17** n = 835	0.25** n = 834	0.65** n = 680	—	—
TOSREC	0.19** n = 823	0.12** n = 823	0.08* n = 822	0.40** n = 669	0.39** n = 821	—
Math fluency	0.25** n = 658	0.07 n = 658	0.14** n = 658	0.37** n = 531	0.30** n = 662	0.48** n = 656

Note. Parent-reported WM = parent-reported working memory; FCAT = Florida Comprehensive Assessment Test reading subtest; GM = Gates MacGinitie Reading Tests comprehension subtest; TOSREC = Test of Silent Reading Efficiency and Comprehension; Math Fluency = Woodcock Johnson-III Tests of Achievement math fluency subtest. Correlations were calculated using data regressed on age, age-squared, and gender. The sample size reflects individuals.
* $p < .05$. ** $p < .001$.

measures (e^2 = .18–.27). Univariate genetic and environmental estimates were also calculated for the latent factors for parent-reported EF and reading. The results indicate that both latent factors have significant genetic influences (h^2 = .44, .93), the reading factor has significant shared environmental influences (c^2 = .54), and both have very small nonshared environmental influences (e^2 = .07, .02), underscoring the high reliability of the latent variables.

The path estimates and 95% confidence intervals from the four trivariate Cholesky decomposition models are presented in Figures 2–5. Significant path estimates based on 95% confidence intervals that did not bound zero are denoted by solid lines, and nonsignificant path estimates are indicated by dotted lines (Neale, Boker, Xie, & Maes, 1997). The factor loadings for the FCAT, GM, and TOSREC onto the reading factor (.86, .78, and .53, respectively) are presented in Figures 2–5, and the factor loadings for parent-reported WM, shifting, and inhibition onto the parent-reported EF factor (.80, .74, .76, respectively) are presented in Figure 5.

Figure 2 depicts the model analyzing the etiological influences among and on parent-reported WM, a latent factor of reading, and math fluency (Log likelihood = −4871.26; AIC = 9802.52; BIC = 9924.64; df = 100; $\chi^2(100, N = 443) = 1750.83$, $p < .001$; RMSEA = 0.13, 90% CI [0.12, 0.15]; CFI = 0.77; TLI = 0.79). The results from this model showed significant genetic influences underlying the association among parent-reported WM, reading, and math fluency (path estimates of .79, .38 and .30, respectively). Beyond the genetic influences on the overlap among all three, there were significant unique genetic influences on reading (path estimate of .65) and on math fluency (path estimate of .58). The model also indicated that there were significant shared environmental influences on the overlap between reading and math fluency (path estimates of .82 and .25), and significant independent shared environmental influences on math fluency alone (path estimate of .54). Finally, the model showed significant nonshared environmental influences between parent-reported WM and reading (path estimates of .64 and .14), and on math fluency alone (path estimate of .47).

Figure 3 depicts the second Cholesky decomposition model analyzing the etiological influences among and on parent-reported shifting, the reading factor, and math fluency (Log likelihood = −4870.28; AIC = 9800.56; BIC = 9922.68; df = 100; $\chi^2(100, N = 443) = 1738.09$, $p < .001$; RMSEA = 0.13, 90% CI [0.12, 0.14]; CFI = 0.78; TLI = 0.80). The results indicated significant genetic overlap between parent-reported shifting and reading (path estimates of .87 and .29), reading and math fluency (path estimates of .70 and .40), and on math fluency alone (path estimate of .62). Significant independent shared environmental influences were found on reading alone (path estimate of .82) and math fluency alone (path estimate of .47). Finally, the model showed nonshared environmental influences on parent-reported shifting alone (path estimate of .51), and on math fluency alone (path estimate of .47).

Figure 4 depicts the third Cholesky decomposition model analyzing the etiological influences among and on parent-reported inhibition, the reading factor, and math fluency (Log likelihood = −4889.44; AIC = 9838.87; BIC = 9960.99; df = 100; $\chi^2(100, N = 443) = 1706.83$, $p < .001$; RMSEA = 0.13, 90% CI [0.12, 0.15]; CFI = 0.76; TLI = 0.78). The results indicated significant genetic influences underlying the association among parent-reported inhibition, reading, and math fluency (path estimates of .85, .26, and .22, respectively). Beyond significant genetic influences among all three, there were significant genetic influences on the relation between reading and math fluency (path estimates of .64 and .28) and unique genetic influences on math fluency alone (path estimate of .63). The model also indicated significant unique shared environmental influences on reading alone (path estimate of .69) and math fluency alone (path estimate of .50). Finally, the model showed significant unique nonshared environmental influences between parent-reported inhibition and reading (path estimates of .57 and .05) and on the overlap of reading and math fluency (path estimates of .09 and .47).

Figure 5 presents the fourth Cholesky decomposition model analyzing the etiological influences among and on a latent

Table 3
Intraclass and Cross-Twin Cross-Trait Correlations

Measure	Zygosity	Parent-reported WM	Parent-reported shifting	Parent-reported inhibition	FCAT	GM	TOSREC	Math fluency
Parent-reported WM	MZ	0.59 $p < .0001$ $n = 330$	—	—	—	—	—	—
	DZ	0.20 $p < .0001$ $n = 516$	—	—	—	—	—	—
Parent-reported shifting	MZ	0.51 $p < .0001$ $n = 330$	0.73 $p < .0001$ $n = 330$	—	—	—	—	—
	DZ	0.31 $p < .0001$ $n = 516$	0.36 $p < .0001$ $n = 516$	—	—	—	—	—
Parent-reported inhibition	MZ	0.43 $p < .0001$ $n = 300$	0.50 $p < .0001$ $n = 330$	0.65 $p < .0001$ $n = 330$	—	—	—	—
	DZ	0.23 $p < .0001$ $n = 515$	0.27 $p < .0001$ $n = 515$	0.22 $p < .0001$ $n = 514$	—	—	—	—
FCAT	MZ	0.15 $p = .0103$ $n = 283$	0.19 $p = .0013$ $n = 283$	0.16 $p = .0084$ $n = 283$	0.77 $p < .0001$ $n = 284$	—	—	—
	DZ	0.11 $p = .0245$ $n = 408$	0.02 $p = .6262$ $n = 408$	0.16 $p = .0011$ $n = 408$	0.63 $p < .0001$ $n = 406$	—	—	—
GM	MZ	0.11 $p = .0556$ $n = 332$	0.10 $p = .0916$ $n = 332$	0.13 $p = .0176$ $n = 332$	0.63 $p = .3835$ $n = 282$	0.67 $p < .0001$ $n = 336$	—	—
	DZ	0.14 $p = .0015$ $n = 497$	0.11 $p = .0133$ $n = 497$	0.17 $p = .0002$ $n = 496$	0.44 $p < .0001$ $n = 394$	0.53 $p < .0001$ $n = 502$	—	—
TOSREC	MZ	0.10 $p = .0863$ $n = 325$	0.11 $p = .0552$ $n = 325$	0.09 $p = .0759$ $n = 325$	0.38 $p < .0001$ $n = 276$	0.33 $p < .0001$ $n = 329$	0.81 $p < .0001$ $n = 328$	—
	DZ	0.04 $p = .0234$ $n = 492$	0.07 $p = .1130$ $n = 492$	0.02 $p = .6134$ $n = 491$	0.26 $p < .0001$ $n = 389$	0.21 $p < .0001$ $n = 486$	0.61 $p < .0001$ $n = 496$	—
Math fluency	MZ	0.14 $p = .0210$ $n = 269$	0.08 $p = .1876$ $n = 269$	0.08 $p = .2145$ $n = 269$	0.39 $p < .0001$ $n = 223$	0.27 $p < .0001$ $n = 272$	0.46 $p < .0001$ $n = 268$	0.76 $p < .0001$ $n = 268$
	DZ	0.02 $p = .6457$ $n = 388$	0.05 $p = .3059$ $n = 388$	0.02 $p = .7496$ $n = 388$	0.25 $p < .0001$ $n = 307$	0.14 $p = .0054$ $n = 388$	0.28 $p < .0001$ $n = 386$	0.50 $p < .0001$ $n = 376$

Note. MZ = monozygotic twins; DZ = dizygotic twins, Parent-reported WM = parent-reported working memory; FCAT = Florida Comprehensive Assessment Test reading subtest; GM = Gates MacGinitie Reading Tests comprehension subtest; TOSREC = Test of Silent Reading Efficiency and Comprehension; Math Fluency = Woodcock Johnson-III Tests of Achievement math fluency subtest. Correlations were calculated using data regressed on age, age-squared, and sex. Sample size reflects individuals.

factor of parent-reported EF (comprised of parent-reported WM, shifting, and inhibition measures), the reading factor, and math fluency (Log likelihood = −6863.31; AIC = 13810.61; BIC = 13981.59; $df = 196$; $\chi^2(196, N = 443) = 2838.67$, $p < .001$; RMSEA = 0.11, 90% CI [0.10, 0.12]; CFI = 0.80; TLI = 0.81). The results from this model showed significant genetic influences underlying the association among parent-reported EF, reading, and math fluency (path estimates of .92, .38 and .25). Beyond the genetic influences on the overlap among all three, there were significant unique genetic influences on reading alone (path estimate of .61) and math fluency alone (path estimate of .61). The model also indicated that there were significant shared environmental influences on the overlap between reading and math fluency (path estimate of .80 and .24), and significant independent shared environmental influences on math fluency alone (path estimate of .51). Finally, the model showed significant nonshared environmental influences on the relation between parent-reported EF and reading (path estimates of .25 and .13), and on math fluency alone (path estimate of .47).

Discussion

The present work was the first to use a genetically sensitive design to directly quantify the etiological influences on and among parent-reported EF, reading, and math fluency within a hybrid model framework. Overall, despite the low to moderate correlations of parent-reported EF with reading and math in our sample,

Table 4
Univariate Genetic and Environmental Estimates [95% Confidence Interval]

Measure	h^2	c^2	e^2
Parent-reported WM	.73 [.46, .74]	—	.27 [.33, .52]
Parent-reported shifting	.74 [.63, .87]	—	.26 [.22, .33]
Parent-reported inhibition	.79 [.55, .83]	—	.21 [.27, .43]
Parent-reported EF factor	.93 [.78–1.00]	—	.07 [.004, .17]
Reading factor	.44 [.29, .65]	.54 [.29, .67]	.02 [.003, .05]
FACT	.42 [.25, .59]	.40 [.23, .58]	.19 [.14, .25]
GM	.35 [.01, .69]	.35 [.03, .67]	.31 [.20, .46]
TOSREC	.44 [.20, .69]	.38 [.15, .69]	.18 [.11, .28]
Math fluency	.53 [.27, .79]	.28 [.01, .55]	.22 [.15, .29]

Note. Parent-reported WM = Parent-reported working memory; Parent-reported EF = parent-reported executive functioning; FCAT = Florida Comprehensive Assessment Test reading subtest; GM = Gates MacGinitie Reading Tests comprehension subtest; TOSREC = Test of Silent Reading Efficiency and Comprehension; Math Fluency = Woodcock Johnson-III Tests of Achievement math fluency subtest. Significance is denoted when the 95% confidence interval does not bound zero. Parent-reported EF factor is the latent factor for parent-reported executive functioning that captures working memory, shifting, and inhibition. Reading factor is the latent factor for reading that includes the FCAT, the GM, and the TOSREC. Given that ICCs supported an ADE model for parent-reported EF, but we were interested in the overlap of parent-reported EF with reading and math, which support an ACE model, an AE-only model was modeled for parent-reported EF.

the correlations that *did* exist were explained by shared genetic influences among parent-reported EF, reading, and math. These findings align with the hybrid model's tenet that the cognitive and behavioral levels of learning-related abilities are linked by overlapping, general, etiological influences. Also in support of the hybrid model's tenet that unique abilities, such as reading and math, are distinguished by domain-specific risk and protective factors, unique genetic and environmental influences were also found for all three domains. Previous work has highlighted domain-specific abilities that underlie parent-reported EF (planning), reading (print knowledge), and math (subitizing), which probably underlie some of this construct-unique variance (Purpura, Schmitt, & Ganley, 2017), but these specific abilities were not available in this sample and could not be tested.

Overall, our results support the idea that reading and math abilities are distinct but related skills that co-occur because of common etiological risk and protective factors and that parent-reported EF may serve as a cognitive-level skill that partially links the etiological and behavioral levels. The one exception to the similarities found across our models was for parent-reported shifting, which had common genetic influences with reading only, in contrast to the domain-general genetic influences found for parent-reported WM and inhibition with reading and math. Given our finding that the phenotypic correlation between parent-reported shifting and math fluency was not statistically significant, a significant etiological association between the two domains would not have been possible. Interestingly, the lack of a statistically significant association between parent-reported shifting and math fluency has been found in previous phenotypic work using the same BRIEF shifting scale and the same math fluency measure (Clark et al., 2010). However, the present study differed from this previous work by finding a statistically significant association between parent-reported shifting and reading (Clark et al., 2010). Importantly, despite the lack of significant etiological overlap between parent-reported shifting and math fluency, there are indications in our findings that the two domains may be genetically associated. For example, our results showed that the path estimate for the common genetic variance between parent-reported shifting and math fell within the confidence intervals of the estimates for parent-reported WM and inhibition to math. Furthermore, it is clear that all parent-reported EF components, including shifting, had a high factor loading onto the parent-reported EF factor, indicating that there is common executive variance captured by parent-reported shifting that contributes to the common genetic variance observed among parent-reported EF, reading, and math.

The generally low magnitude correlations found for parent-reported EF with reading and math in the present sample may be attributable to our use of the BRIEF, which is a report-based measure that assesses EF as it is manifested behaviorally. Such a behavioral parent-reported EF measure may reduce the task impurity problem inherent in many cognitive performance-based EF indices (McAuley et al., 2010). For example, a task-based cognitive EF measure that requires reading would be more strongly correlated with a reading assessment but also make it impossible to distinguish which aspects of task performance are attributable to reading versus EF ability because of shared method variance (van der Sluis, de Jong, & van der Leij, 2007). In addition, the increase in measurement error with a questionnaire versus a tightly controlled behavioral measure may also result in a weaker correlation between parent-reported EF and reading or math. Importantly, the phenotypic correlations should be taken into account when interpreting our etiological results because, although genetic influences are significant among parent-reported EF, reading, and math, the magnitude of the correlations they are explaining are not large.

Controlling for Parent-Reported Problem Behaviors

In an attempt to remove some potential rater bias from parent-reported BRIEF scores, we also ran supplemental models that controlled for parent-reported problem behaviors. Compared with our main analyses, our supplemental results were similar, with changes in the statistical significance of a few nonshared environmental and genetic pathways. These changes resulted in a reduction in the overall error, higher nonshared environmental path estimates, and a loss of significance in the common genetic path-

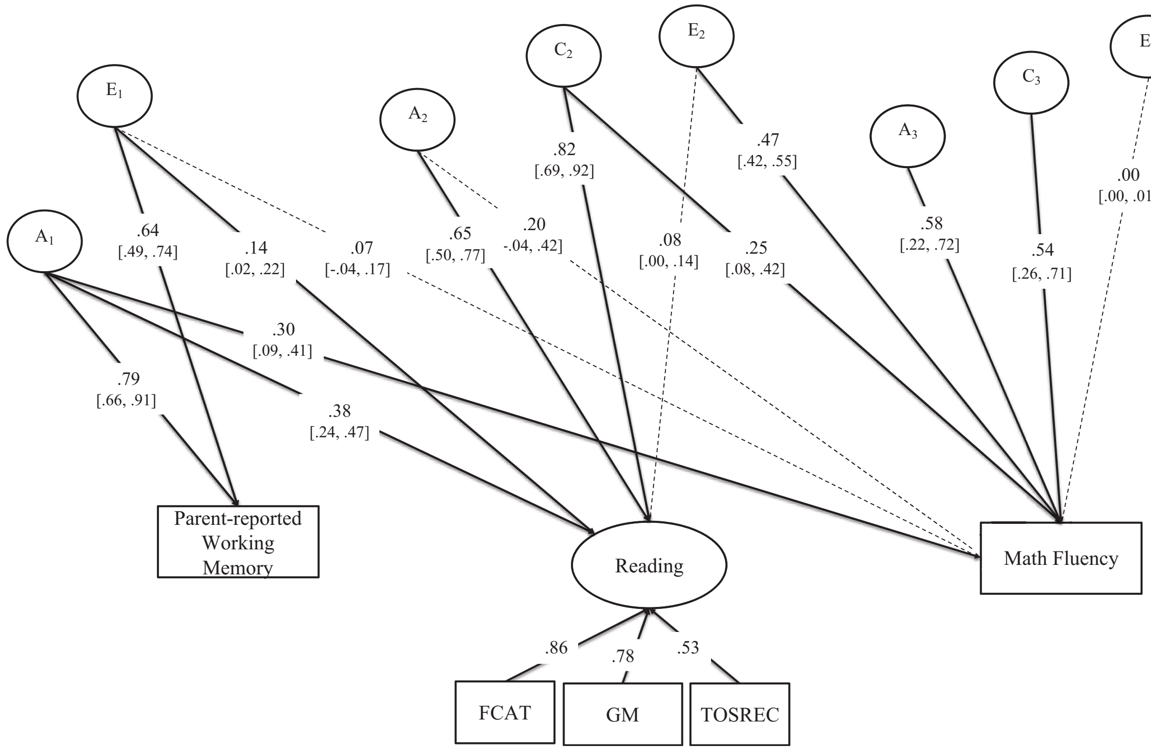

Figure 2. Trivariate Cholesky modeling parent-reported working memory, reading, and math fluency. Standardized path estimates are presented. Path estimates' 95% confidence intervals are reported in brackets. Solid lines represent confidence intervals that do not bound zero, indicating a statistically significant path estimate. FCAT = Florida Comprehensive Assessment Test reading subtest; GM = Gates MacGinitie Reading Tests comprehension subtest; TOSREC = Test of Silent Reading Efficiency and Comprehension; Math Fluency = Woodcock Johnson-III Tests of Achievement math fluency subtest.

ways between parent-reported EF and math (although the estimates did not change much) for the parent-reported inhibition and parent-reported EF factor models. Based on the generalist genes hypothesis, we expected the co-occurrence of EF, reading, and math abilities to be driven mainly by common genetic influences (Plomin & Kovas, 2005), which serve as a common etiological risk or protective factor within a hybrid model framework (van Bergen et al., 2014). Although this was true for the overlap of reading and parent-reported EF in both the main and supplemental analyses, and for all except the parent-reported shifting model in the main analyses, this was demonstrated only for the parent-reported WM supplemental model. This loss of statistical significance in the parent-reported inhibition and latent EF factor supplemental models indicates that the genetic correlations for these models were attributable to common genetic variance between children's general behavioral problems and math.

Although our intention was to control for rater bias in order to zero in on children's cognitive EF skills, it appears that we may have also taken out true variance in child behavior that is important for capturing report-based EF. Overall, our supplemental results provide evidence that, rather than EF itself, report-based EF assessments may capture self-regulatory abilities enabled by EF instead (Malanchini et al., 2018; Toplak et al., 2013). This aligns with previous work showing that report-versus performance-based EF assessments both uniquely predict reading and math when modeled together, capturing different aspects of EF (Gerst, Cirino, Fletcher, & Yoshida, 2017). Our findings support the notion that report-based measures seem to tap into real-world applied skills that EF facilitates (i.e., behavioral regulation), and performance-based EF measures may be more likely to capture the optimal performance of EF itself (Nęcka et al., 2018). In the same vein as performance-based EF assessment, our findings highlight the importance of measuring report-based EF and self-regulatory ability using more than one assessment in order to differentiate cognitive EF skills from parents' general perceptions of their children's behavior (McCoy, 2019). In accordance with previous studies that have found that report-based measures have limited associations when raters are from different contextual settings, like the classroom versus the home environment (Achenbach, McConaughy, & Howell,1987), and that both parent and teacher reports have predictive value (Verhulst, Koot, & Van der Ende, 1994), it may also be important to include more than one informant for each report-based measure, like both parents and a teacher.

When considering the changes in the etiological findings from the main analyses to the supplemental analyses, it is important to look closely at the differences in the items that comprise each parent-reported BRIEF scale and how closely they may or may not align with a parent-report scale of problem

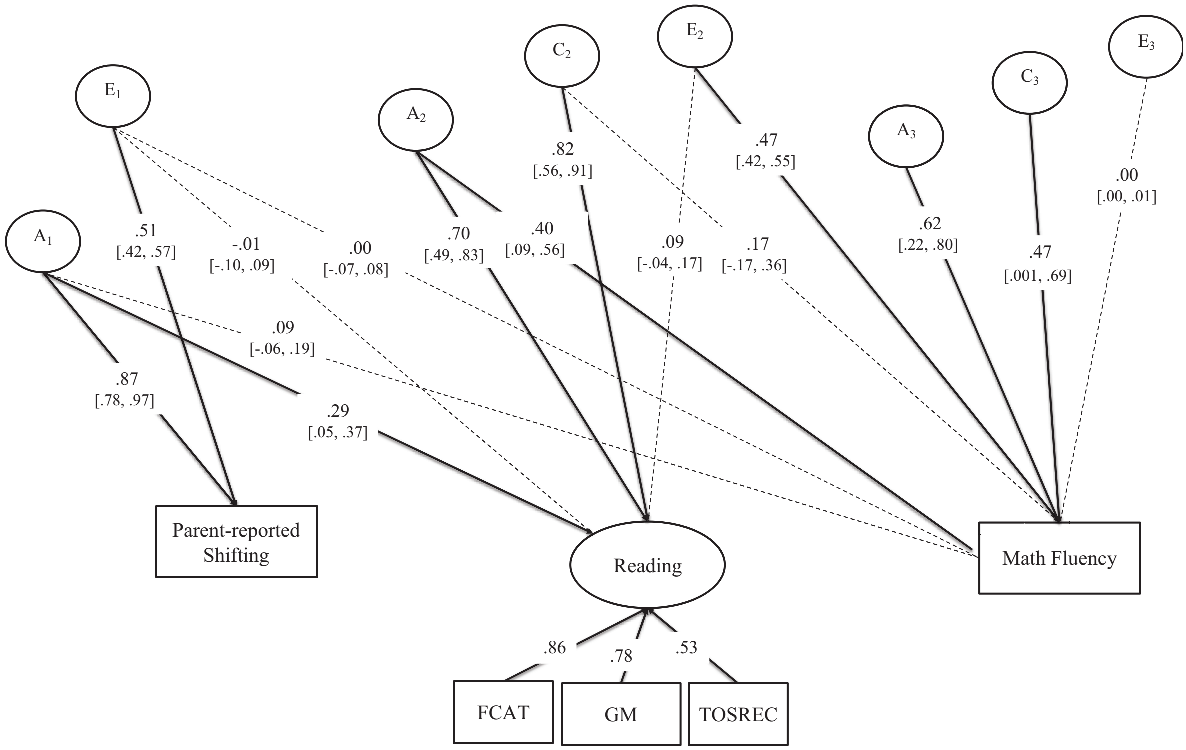

Figure 3. Trivariate Cholesky modeling parent-reported shifting, reading, and math fluency. Standardized path estimates are presented. Path estimates' 95% confidence intervals are reported in brackets. Solid lines represent confidence intervals that do not bound zero, indicating a statistically significant path estimate. FCAT = Florida Comprehensive Assessment Test reading subtest; GM = Gates MacGinitie Reading Tests comprehension subtest; TOSREC = Test of Silent Reading Efficiency and Comprehension; Math Fluency = Woodcock Johnson-III Tests of Achievement math fluency subtest.

behaviors. Focusing first on the inhibition and shifting scales of the BRIEF, both scales include items related to behavioral dysregulation, outbursts, and difficulty adjusting to change, which can all be characterized as problem behaviors. This makes sense, as children with behavioral problems are more likely to show EF problems (Pennington & Ozonoff, 1996), and behavioral outbursts are one of the only ways to easily observe the manifestation of deficient EF abilities from the outside. On the other hand, the parent-reported WM scale includes items related to children's difficulties remembering things when there is more than one important piece of information to hold in memory or problems concentrating on relevant information. These items are not likely to manifest as behavior problems. Instead, deficiencies in these kinds of EF-related abilities are more likely just to be inconvenient and potentially frustrating to children and parents rather than disruptive in the same manner as behavioral dysregulation. Thus, the fact that WM had the lowest magnitude correlation with parent-reported problem behaviors relative to the other parent-reported EF skills is not surprising (r = .52 compared with .57 for shifting and .65 for inhibition).[1] This lack of common variance between parent-reported WM and parent-reported problem behaviors may also be one of the reasons why the genetic underpinnings of WM, reading, and math did not fluctuate after the BRIEF scores were residualized.

Shared Environmental Results

In line with prior investigations using the FTP sample, our results showed relatively greater shared environmental variance for achievement measures than other studies conducted with less diverse twin samples (Taylor et al., 2010). In contrast to other twin work assessing math fluency (Hart, Petrill, & Thompson, 2010; Petrill et al., 2012), the results here showed significant shared environmental influences on math fluency. The pattern of results found here, with lower genetic and higher shared environmental estimates, is most likely due to the fact that our sample has a wide distribution of socioeconomic status (SES), with about one third of our sample qualifying as low SES based on household income and maternal education level.

[1] The correlation contrast test (Dunn & Clark, 1971; Meng, Rosenthal, & Rubin, 1992) was used to determine whether the correlation between parent-reported WM and parent-reported problem behaviors was statistically significantly different from the correlations of parent-reported shifting and inhibition with parent-reported problem behaviors. Results indicated the correlation between parent-reported WM and parent-reported problem behaviors (r = .52) was statistically significantly less than the correlations between parent-reported shifting and parent-reported problem behaviors (r = .57) and parent-reported inhibition and parent-reported problem behaviors (r = .65; z = −1.78, p = .04 and z = −4.91, p = .00, respectively).

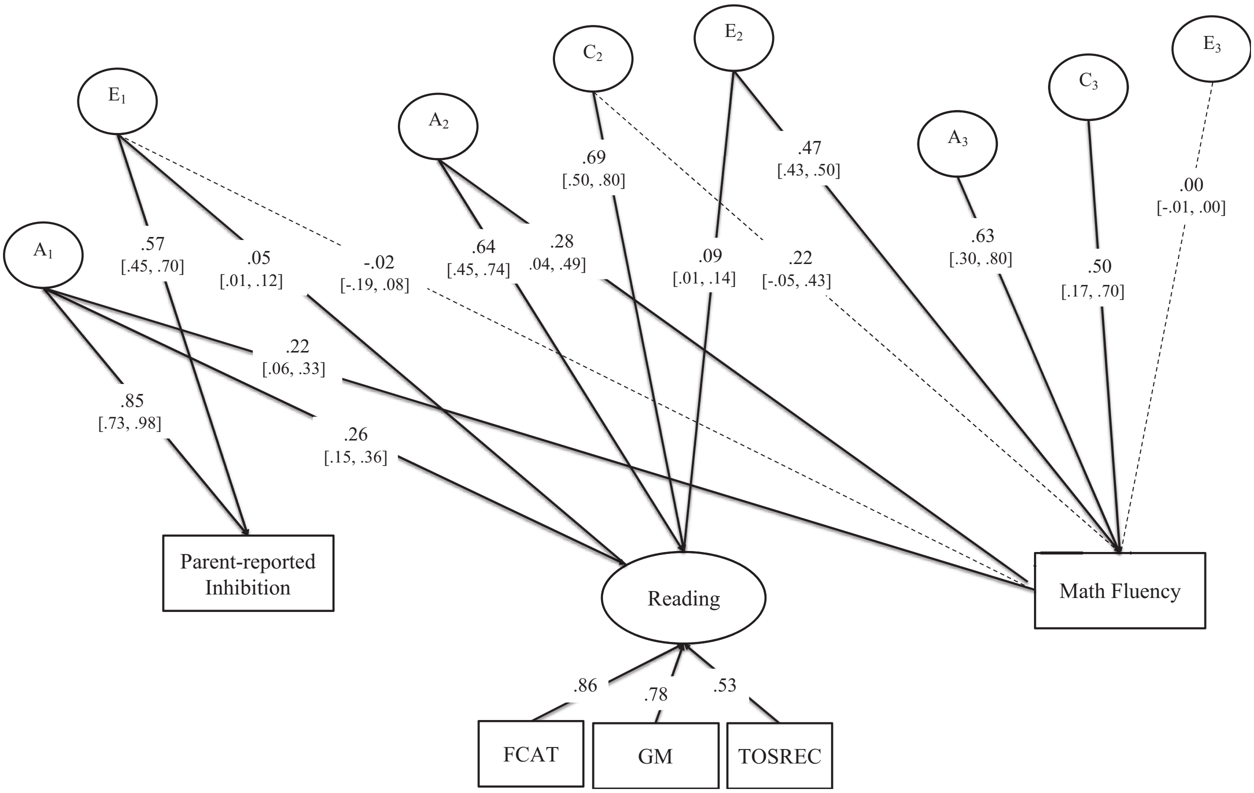

Figure 4. Trivariate Cholesky modeling parent-reported inhibition, reading, and math fluency. Standardized path estimates are presented. Path estimates' 95% confidence intervals are reported in brackets. Solid lines represent confidence intervals that do not bound zero, indicating a statistically significant path estimate. FCAT = Florida Comprehensive Assessment Test reading subtest; GM = Gates MacGinitie Reading Tests comprehension subtest; TOSREC = Test of Silent Reading Efficiency and Comprehension; Math Fluency = Woodcock Johnson-III Tests of Achievement math fluency subtest.

This notion is based on Bronfenbrenner and Ceci's (1994) seminal article on the bioecological model, which posited that environmental conditions and processes can influence the heritability of certain traits, with disadvantaged environments (i.e., low SES) showing higher shared environmental influences and a lower degree of genetic influences than more advantaged (i.e., high SES) environments due to differences in stability and resource-availability. Thus, these differences in heritability compared to other twin work are probably due to low SES households, which have greater environmental variation than high SES households, being represented in our sample.

Outside of the association with parent-reported EF, our modeling also supported the existence of cross-domain shared environmental influences between reading and math ability, which aligns with recent work on the etiological associations among task-based EF, reading, and math (Fujisawa et al., 2019). This finding also aligns with evidence that both reading and math are taught in a number of environments that make siblings more alike, including in school, and often in the home (Skwarchuk, Sowinski, & LeFevre, 2014). Based on the importance of formal and informal instructional environments for reading and math development shown in phenotypic work (Skwarchuk et al., 2014), and our etiological finding that common shared environmental influences exist between reading and math, the present study also provides evidence to support the claim that future genetically sensitive studies should investigate etiological relations across multiple, heterogeneous twin samples in order to obtain more generalizable results (Daucourt et al., 2020).

Limitations

The present study is not without limitations. Given that the primary objective of the FTP is the assessment of reading outcomes, the math data available was limited to just one timed math measure. Importantly, the advantage of the math measure used was that by not including any word problems, our math measure was likely not subject to task impurity and only captured variance attributable to math and not reading ability. Additionally, given that our measurement of EF was parent-report, and parents may have a different concept of their children's EF abilities, direct measurement techniques that employed an outside observer may have reduced potential biases, like social desirability. However, recent reports have shown that since observational EF measures are highly structured and controlled, questionnaire-based EF measurement may be a more accurate means of capturing typical, rather than optimal, EF performance, which is probably more indicative of the EF children employ in everyday settings, like the classroom

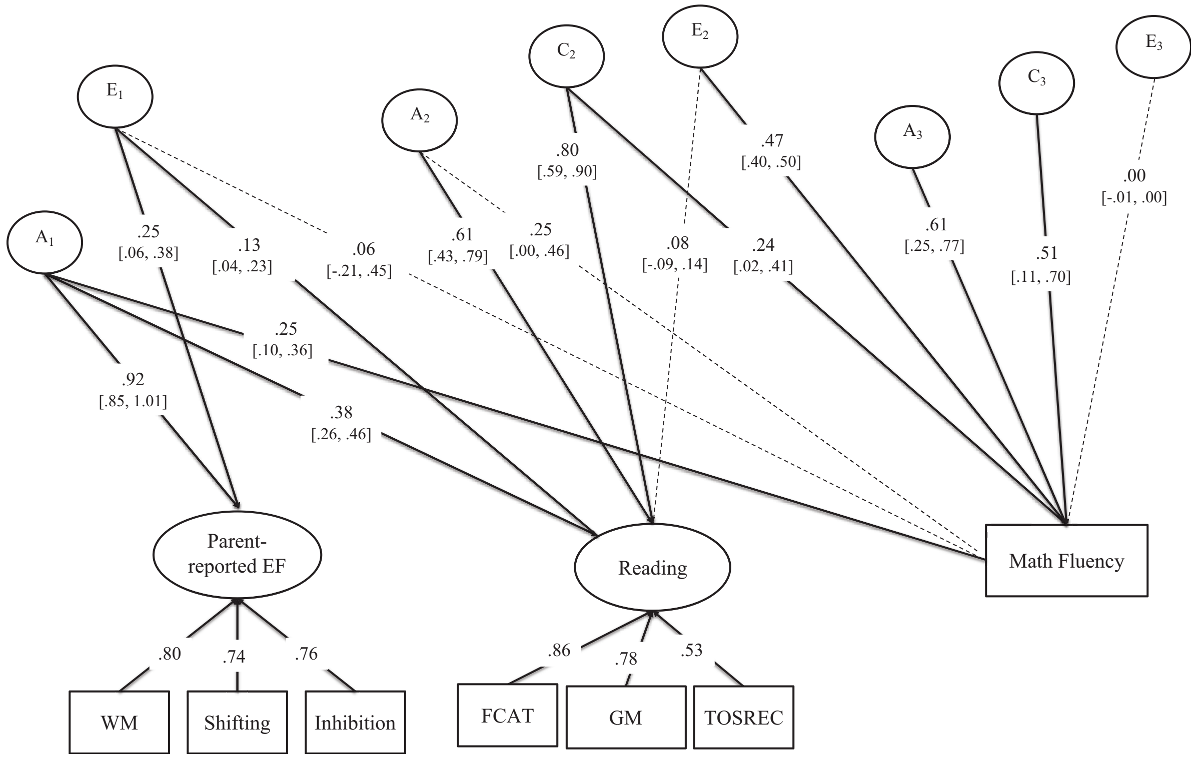

Figure 5. Trivariate Cholesky modeling parent-reported executive functioning, reading, and math fluency. Standardized path estimates are presented. Path estimates' 95% confidence intervals are reported in brackets. Solid lines represent confidence intervals that do not bound zero, indicating a statistically significant path estimate. Parent-reported EF = parent-reported executive functioning; Parent-reported WM = parent-reported working memory; FCAT = Florida Comprehensive Assessment Test reading subtest; GM = Gates MacGinitie Reading Tests comprehension subtest; TOSREC = Test of Silent Reading Efficiency and Comprehension; Math Fluency = Woodcock Johnson-III Tests of Achievement math fluency subtest.

(Malanchini et al., 2018; McAuley et al., 2010; Toplak et al., 2013). Our results showing that parent-reported EF did not account for all the common variance between reading and math fluency suggest that there are other factors that account for the co-occurrence of reading and math difficulties for which we did not account. Based on the common shared environmental influences between reading and math, there are likely to be contextual factors at play that we did not measure in the present study, like the home learning environment (Skwarchuk et al., 2014). It must also be noted that EFs (captured by task-based measurement) are both phenotypically and genetically correlated with a range of other domain-general cognitive abilities, like processing speed and general intelligence (Engelhardt et al., 2016; Malanchini et al., 2018), and the modeling used in current report did not explicitly address the roles of these EF-related abilities. Finally, although they were not modeled here, it is also important to note that dominance genetic influences due to sibling contrast or rater bias effects may have been influencing our parent-reported EF measures, but the current analysis does not allow us to make inferences about them.

Conclusion

Genetically sensitive studies on learning abilities, like the present work, are needed to inform the development of identification and remediation procedures across many learning disabilities. For example, when shared etiologies are found across subject areas, like the ones found here for reading and math, it indicates that the potential exists for interventions to target more than one disability at once. In line with the hybrid model framework, the identification of common cognitive risk factors among learning domains also helps identify which domain-general variables to include in test batteries used to identify children at risk for developing learning problems in one or more domains (Vanbinst, van Bergen, Ghesquière, & De Smedt, 2020). Of equal importance, the finding of unique etiological risk factors also provides support for the need to target domain-specific skills for remediation within each deficient domain. According to our results, the hybrid model is a viable framework for continued research on the multiple levels of influence on learning disabilities and will help inform the development of future interventions to help struggling children. Our results also support previous work demonstrating important empirical differences in report- versus performance-based EF assessment methods. Although we found genetic links between report-based EF, reading and math, we also found evidence that our report-based EF measures were tapping into children's general behavioral regulation abilities. Based on these findings, it appears that report-based EF measures are well suited to provide a snapshot of children's EF ability in a real-world setting.

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